SENSOR-LINKED SIMULATION FOR EMERGENCY RESPONSE

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ABSTRACT

The FireGrid project defines a vision whereby computational fire simulation tools are linked to real-time information derived from sensors in a building, providing potentially valuable information to an end user in terms of the current fire conditions, and, via steered models, their *possible* evolution. This paper outlines the "steering" of the simulation by the sensor data, and demonstrates the potential to provide responders with more information than that available solely from the sensor measurements. A hypothetical example is described, with a coupled model of fire development and human evacuation behaviour used to predict the locations in the building where casualties are most likely to occur.

INTRODUCTION

The modern built environment is rich in sensors which, in addition to their normal building management functions, can also be exploited to provide useful information in the event of a fire occurring. A detailed knowledge of the evolving conditions during a fire emergency can in theory be used to improve the response, both by the occupants and also by fire-fighters. The motivation for the FireGrid project [1,2] came from incidents such as the terrorist attacks on the World Trade Center in New York, and the building collapses that occurred as a result. The vision of the FireGrid project is to couple computational fire simulation tools with real-time sensor information in order to predict the future development of the fire and provide advance warning of extreme events such as structural failure. However the same approach can also be employed to advantage in less severe fires, by giving fire-fighters a better picture of what conditions they may face inside the building. In this paper we shall describe an example where the probability of fatalities is estimated for different locations within the building, enabling a search and rescue strategy to be prioritised.

STEERING OF MODELS USING BAYESIAN INFERENCE

Mathematically, Bayes' Theorem is most often expressed in the following form:

$$P(A \mid B) = \frac{P(B \mid A).P(A)}{P(B)} \qquad \{1\}$$

where $P(A)$ is the probability of event "A" occurring (often termed the "prior" probability), $P(A|B)$ is the conditional probability of A occurring, given that event "B" occurs (often termed the "posterior" probability). Similarly, $P(B)$ is the probability of B, and $P(B|A)$ is the conditional probability of B given that A occurs. The "prior" probability is updated in the light of fresh evidence (the occurrence of event B) to give the posterior probability.

If the events A and B both have a range of different outcomes, then following the observation of a particular outcome B_i we can write Bayes' Theorem as follows:

$$P(A_j \mid B_i) = \frac{P(B_i \mid A_j).P(A_j)}{\sum_k P(B_i \mid A_k).P(A_k)} \qquad \{2\}$$

where the denominator is an alternative way of expressing $P(B_i)$. If we define the likelihood function $L(B_i|A_j)$ as

$$L(B_i \mid A_j) = \frac{P(B_i \mid A_j)}{\sum_k P(B_i \mid A_k).P(A_k)} \qquad \{3\}$$

then equation {2} can be simplified to

$$P(A_j \mid B_i) = L(B_i \mid A_j).P(A_j) \qquad \{4\}$$

i.e. the posterior probability = the prior probability x the likelihood function. This calculation of the posterior probability estimate is known as Bayesian Inference.

A simple example may illustrate the process. Suppose we have a fire in a room, adjacent to a corridor that contains a smoke alarm. Let us further assume that the chance of detecting the fire at a given time is 50% if the connecting door is open, but only 1% if the door is closed (some leakage of smoke around the edges may occur). We will use the notation A_1 = door open, A_2 = door closed, B_1 = detection, B_2 = no detection. If we have no prior information regarding the state of the door, we assign $P(A_1) = P(A_2) = 0.5$. Substituting into equation {3}, the likelihood $L(B_1|A_1)$ of detecting the fire if the door is open is 0.50 / (0.50 x 0.5 + 0.01 x 0.5), which equals 1.96. Hence, from equation {4}, the inferred probability that the door is open, given that the detector operated, is 1.96 x 0.5 = 0.98. If on the other hand there is no detection, the likelihood $L(B_2|A_1)$ of <u>not</u> detecting the fire if the door is open is 0.50 / (0.50 x 0.5 + 0.99 x 0.5), which equals 0.67, and hence the inferred posterior probability that the door is open is only 0.33.

In a more realistic and complex building, the link between cause and effect will be less straightforward. In order to derive the likelihood function, we can use fire modelling to predict what the sensor measurements will be, for given input conditions (e.g. combinations of doors open and closed, fire location, rate of fire growth, etc). We can estimate $P(B_i|A_j)$ simply as the number of times a particular sensor observation B_i occurs in the model outputs, divided by the number of times that the model chooses a particular set of input conditions A_j.

With any realistic number of sensors, a perfect match between the model and the actual fire has a negligible probability of arising "by chance" with a lucky choice of the necessary input values A_j. Indeed, how does one define a match for an analogue device such as a thermocouple? We therefore calculate a "fractional match" based on the goodness of fit from a χ^2 test for each set of predicted sensor readings compared to the actual observations. As ν, the number of degrees of freedom (i.e. sensor readings) increases, we can approximate the χ^2 distribution with a Normal distribution of mean ν, variance 2ν.

Note that it is simply impracticable to calculate (and store) the likelihood functions for all possible permutations of the A_j's and B_i's. The model therefore needs to run (many times, very quickly) at the same time as the fire is developing, in order to calculate the likelihood functions for the observed sensor measurements.

If the model is run beyond the time of the current sensor observations, it can be used to predict the future – not just further sensor measurements, but also e.g. how fast the fire is growing, how likely flashover is to occur, whether people will be exposed to smoke and how likely this is to prove fatal, etc. The range of variables that can be predicted obviously depends on the capabilities of the model being used for the task.

Initially, the model will be run with Monte-Carlo sampling that reflects the *a-priori* understanding of the probability distributions for the input variables. As sensor measurements become available, Bayesian Inference is used to update these (posterior) probability distributions. The Monte-Carlo sampling will then use the posterior distributions, rather than the prior distributions. The predictions from the model will also change, in the light of the posterior probabilities. Over time (via observational evidence), the posterior probabilities for the input variables will converge on values that give a close match between the model and the actual fire, up to the current time – and hopefully also a good match for some time into the future as well.

For the FireGrid project, we have used the BRE Monte-Carlo model CRISP, which includes a fully-coupled simulation of fire growth, smoke spread, active and passive fire protection systems, and the egress and interaction of people with the fire environment [3]. Some minor changes to the CRISP source code were required to port the model from a PC to high-performance computers (HPC), specifically Edinburgh's ECDF cluster and the national HPCx machine. Detection of the fire would trigger the transmission of the sensor readings to the HPC over a high-speed data network (the "Grid", hence the project name "FireGrid"). This would also trigger execution of the model, predictions from which would be passed together with the actual sensor measurements to the fire-fighters' Command and Control centre, to inform their operational decisions. A live fire demonstration that integrated all the components of the FireGrid project took place at BRE in October 2008 [2]. Here, a different example application is described for the purpose of illustrating the potential for sensor steering, orientated around the human behaviour aspects of the problem.

APPLICATION EXAMPLE

The application example described in this paper is a hypothetical care home building for the elderly. It was chosen to provide a balance between realism and practicality (given the current state of development of FireGrid). The structure is subdivided into a number of compartments, allowing the risk estimates to be localised.

Scenario description

The floor plan of the hypothetical building is shown in figure 1. Each room has an ID number, from 1 to 33. Rooms 1~14, 17~20 and 23~24 are bedrooms; rooms 15, 16 and 21 are bathrooms; rooms 22, 25, 27 and 30 are store rooms; rooms 26 and 29 are common rooms, room 28 is the staff room, and "rooms" 31~33 are corridors. The room usage affects the probabilities and types of fires that are expected to originate there, and the probability that people will be present.

Doors link the rooms with the corridors. They are identified by the ID's of the rooms they connect (with a further identifier "top", "bottom", "left" or "right" as required. The open ends of corridors 31 and 33 represent the building exits.

There is a smoke detector fitted in each room, identified by the room ID number.

There is one elderly resident for each of the bedrooms (20 in all). 75% of the residents are ambulant, the remainder require assistance to escape. Their behaviour is simple: on hearing the alarm there is a delay while they react (and wake up if necessary), then the ambulant ones escape while the non-ambulant await rescue. It has been assumed for this example that the "actual" fire starts in the late evening, so some residents will be in their bedrooms (awake or asleep), while others are in the common rooms or bathrooms.

There are two members of staff on "night duty". They are assumed to be in the staff room (ID = 28), and when they have heard and reacted to the alarm, they will investigate the fire and attempt first-aid fire-fighting if conditions permit, and warn and rescue residents as necessary.

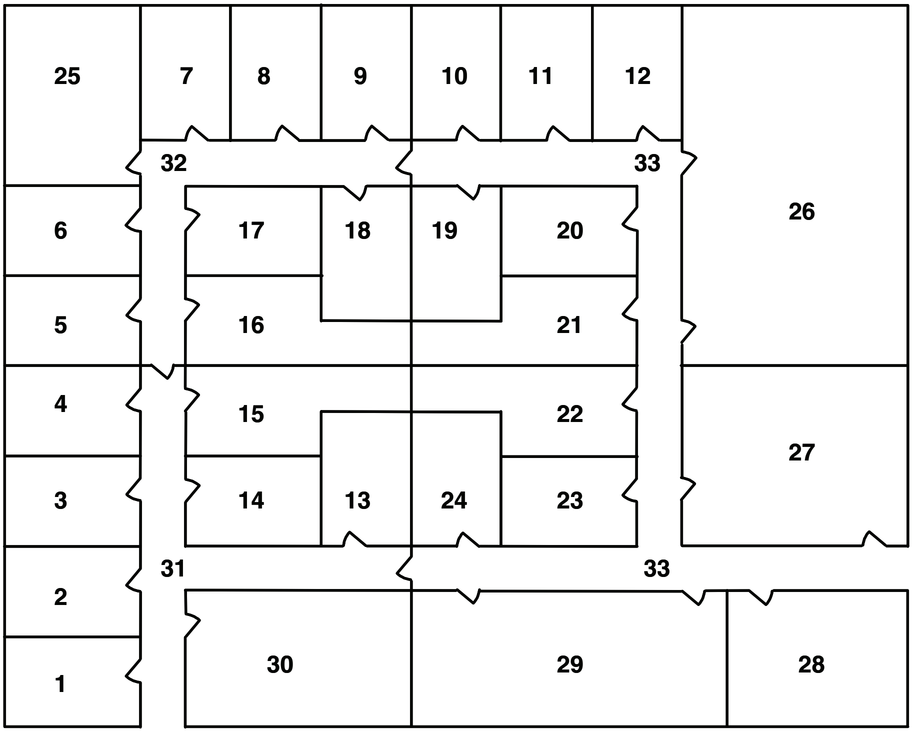

Figure 1. Layout of the hypothetical building example.

The “actual” fire (itself a CRISP simulation) starts in room 25. The doors have self-closers fitted, and it has been assumed *a-priori* for the Bayesian Inference that there is only a 5% chance that each door will (independently) be wedged open. However, for the actual fire, the following doors are open: (25-32), (8-32), (12-33), (16-32), (26t-33) and (32-33). During the fire, the following detectors activate: 25 (0.5min), 32 (1min), 8 (1.5min), 16 (1.5min), 33 (1.5min), 31(2min), 12 (5min), 26 (6.5min), 23 (8min) and 20 (11min). Note that some of these are in rooms where the doors were initially closed, therefore must have been opened (permitting smoke movement) at some time later as a consequence of human behaviour and evacuation.

Results

After 5 minutes the situation is as shown in figure 2. The shaded rooms are those in which a smoke detector has activated in the “actual fire”. The double-ended arrows indicate doors which are wedged open in the “actual fire”. The skull symbols indicate the rooms where the sensor-steered CRISP model is predicting a risk of death per fire that is greater than $1x10^{-3}$, at a time of 30 minutes after ignition (i.e. each CRISP simulation is run for 25 minutes “simulated time” beyond the 5 minutes of sensor data).

The sensor-steered CRISP model was good at identifying which doors were open, but less successful in deducing the properties of the fire (growth rate, etc). Almost certainly it would have helped to record precise detector activation times, rather than simply “on / off” every 30 seconds. However there are still some unresolved issues with the implementation of the Bayesian Inference – some of which come down to the fundamental question “what is the (quantified) goodness of fit between the model and the data?”. Using a χ^2 test to estimate the fit is not perfect, since the test assumes all the measurements are independent, when some clearly are not. Also, the error terms in the χ^2 formula are likely to be dominated by modelling rather than measurement uncertainties. How should the modelling uncertainties be estimated?

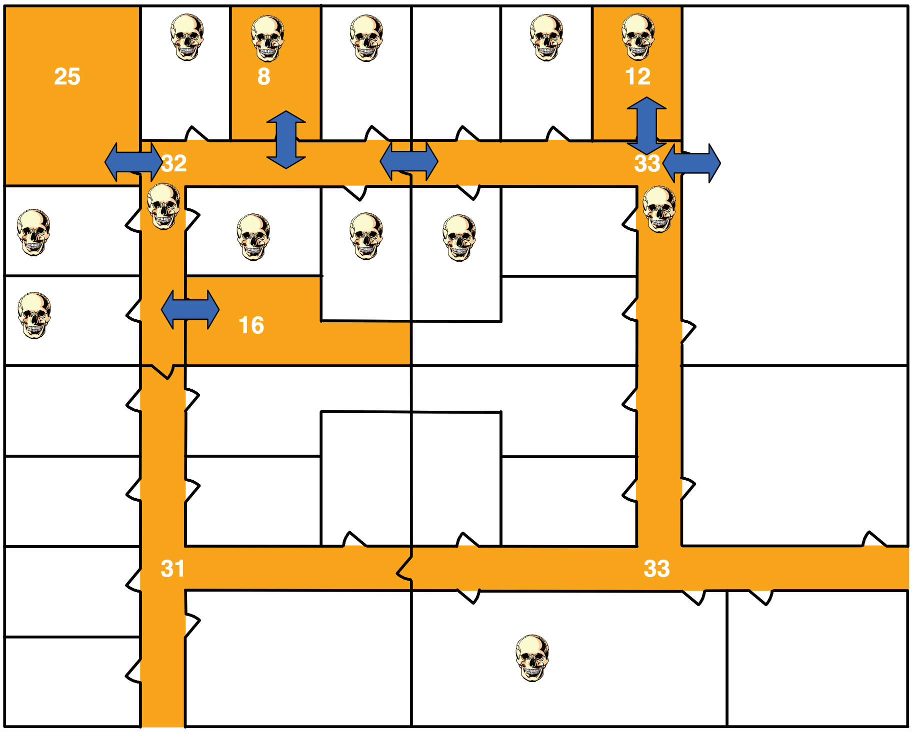

Figure 2. Situation 5 minutes after fire starts. Shading indicates rooms where detection has occurred; double-headed arrows indicates doors initially wedged open, and skull symbols show where deaths are predicted to occur up to 30 minutes after fire start.

Note that the above visualisation is useful for a spatial overview of where the risks are, but gives no information on the relative magnitude of the risks. For this paper, a simple histogram of risk versus room ID can be plotted (figure 3), although this would be impractical for larger multi-compartmented buildings. There is a question whether only deaths should be shown or people with significant non-fatal toxic doses as well. Also note that neither visualisation method shows the uncertainties inherent in the predictions. More work would be required on the visualisation interface to address these issues.

It is striking that the majority of deaths are predicted to occur in the corridors. In order to investigate the possibility that these resulted from the actions of the staff (either exposing themselves to smoke in an effort to rescue dependent occupants, or exposing occupants as a consequence of the rescue attempts), the simulations were repeated without staff intervention. Space does not permit a detailed examination of these results, but it was noted that the overall risk levels were much higher without the staff, and that the risks were distributed over a greater number of rooms.

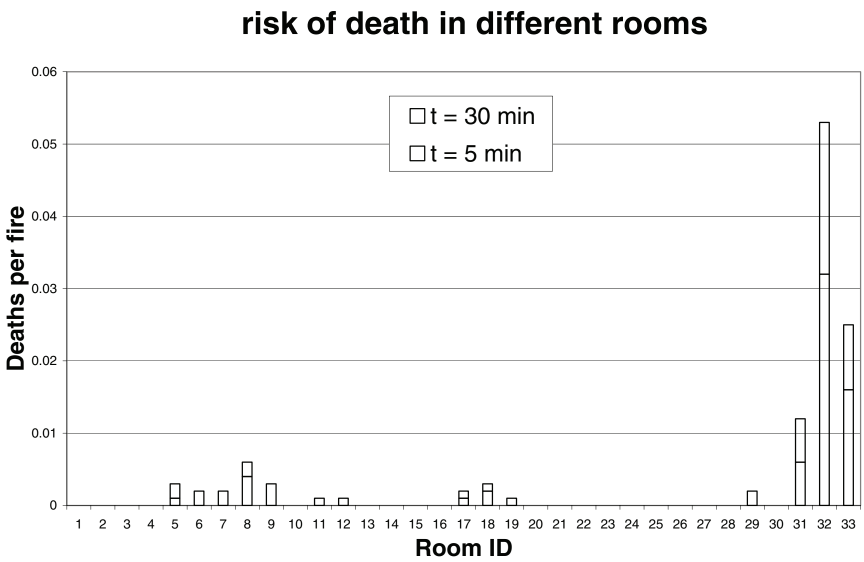

Figure 3. Estimated risk of death per fire in each of the different rooms of the building, 5 minutes and 30 minutes after fire start.

CONCLUSIONS

This paper demonstrates the potential of using a sensor-steered simulation to predict the future evolution of fire emergencies, and thus provide responders with more information than that available solely from the sensor measurements. The results are sensitive to the assumptions made about the human behaviour, so it is important to get this right. In addition to the determination of *a-priori* data for the model, there is also further work to be done on the Bayesian Inference process, and on the visualisation of the results.

The results in this paper are intended solely to demonstrate the sensor-steering process, and should in no way be taken as representative of the hypothetical building occupancy type.

REFERENCES

1. Welch, S., Usmani, A., Upadhyay, R., Berry, D., Potter, S. and Torero, J.L. (2007) “Introduction to FireGrid”, Chapter 1 in The Dalmarnock fire tests: experiments and modelling, Rein, Abecassis-Empis & Carvel (eds.), ISBN: 978-0-9557497-0-4, pp. 7-29.
2. FireGrid cluster homepage has up-to-date information; www.firegrid.org (click “Projects”)
3. Fraser-Mitchell, J.N., "Modelling Human Behaviour within the Fire Risk Assessment Tool CRISP", Fire & Materials 23, 349-355 (1999)

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